Liquidity determination in an order driven market*

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Abstract

We exploit full order level information from an electronic FX broking system to provide a comprehensive account of the determination of its liquidity. We not only look at bid-ask spreads and trading volumes, but also study the determination of order entry rates and depth measures derived from the entire limit order book. We find strong predictability in the arrival of liquidity supply/demand events. Further, in times of low (high) liquidity, liquidity supply (demand) events are more common. In times of high trading activity and volatility, the ratio of limit to market order arrivals is high but order book spreads and depth deteriorate. These results are consistent with market order traders having better information than limit order traders.

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As the recent financial crisis has made clear, the ability to accurately define, measure and explain financial market liquidity is of great importance to academics and market participants alike. Unfortunately, the majority of extant empirical work relies on measures of liquidity that are somewhat narrow in their focus (e.g. bid-ask spreads). The purpose of this paper is to add to the academic understanding of liquidity by providing analysis of those aspects of liquidity which are less well understood. Using order level data from a foreign exchange broking system, we empirically analyze various liquidity measures that include spreads, order book depths and order entry rates. Unlike much previous work in this area, we construct depth measures from across the range of open limit orders, rather than focussing only on quantities available at the best prices. Furthermore, we go on to study the joint determination of our liquidity measures, volatility and transaction activity.

Our empirical work is based on analyzing one week of trading in the USD/DEM spot rate on the Reuters D2000–2 system. Thus our results complement those in much of the extant literature, which are based on analysis of stock market data. FX markets are more fast-paced than stock markets and the evolution of the D2000-2 order book is not interrupted by regular batch auctions caused by daily market opening and closure. The obvious drawback of our data is that they cover only 5 trading days. However, to give some perspective, these 5 days see the submission of around 130,000 orders for trade in USD/DEM with over 20,000 of these being market orders.

Conceptually, the task of measuring liquidity is challenging is due to the fact that there is no generally accepted definition of a “liquid market”. However, Kyle’s (1985) three component classification of liquidity, covering tightness, depth, and resilience, is well–known, and serves as a useful starting point. While empirically implementing Kyle’s definition requires the evaluation of multiple characteristics of a given market, many empirical studies fail to do so, focussing solely on tightness (i.e. spreads). Moreover, most extant analysis of liquidity entirely ignores its dynamic aspects and these aspects are key from the perspective of the construction of optimal execution strategies. A trader with a given amount of an asset to buy or sell is usually given a certain horizon over which the trade must be completed and some benchmark against which transaction costs will be judged. Thus, the trader's problem is to work out when to place an order and what type of orders (market vs. limit) to place. Clearly, the manner in which the trader expects liquidity to respond to the submission of various order types will be crucial in the formation of his strategy.

The central motivation for our work is to provide a comprehensive look at liquidity determination in a specific order driven market. We provide analysis of bid–ask spreads, order book depth and dynamic aspects of liquidity supply and demand determination. As such, our work shares features with two seminal papers that focus on dynamics of liquidity, Biais, Hillion, and Spatt (1995) and Hasbrouck (1999). More recently, with increased availability of order level data from stock exchanges and other security trading platforms, several papers have emerged which also look at measures of liquidity other than the bid-ask spread and which focus on dependencies in order arrivals. An early example is Sandas (2001), who uses order level data from the Swedish Stock Exchange to test a version of the Glosten (1994) model. Hall and Hautsch (2007) study data on 5 stocks from the Australian Stock Exchange and model the arrival intensities of limit and market orders. Some of their results overlap with those we derive from the FX data. They, for example, find that market orders are more likely to arrive when liquidity supply to the order book has recently been strong, as do we. Ranaldo (2004) provides similar results for a sample of stocks from the SWX. Gomber, Schweickert, and Theissen (2004) study the resilience of the market for German stocks traded on Xetra, using an exchange-constructed measure of order book depth. Large (2007) proposes an intensity model for order arrivals and uses that model to study order book resilience for a single LSE traded stock. Last of all, the data we employ here are used in Lo and Sapp (2008) who study the time between the arrivals of certain types of order in an Autoregessive Conditional Duration (ACD) framework.

We perform a range of empirical exercises based on a variety of techniques. We first characterize the D2000–2 liquidity supply process by measuring where limit orders enter the book, how likely execution is for an order entering the book at a given position, and calculating average lifetimes for orders and average limit order sizes.[1] Results show that the most common entry point for fresh liquidity is precisely at the extant best limit price. Further, while orders entering close to the front of the order book have high execution probabilities, our results show that orders entering the book at relatively poor prices also have reasonable probabilities of executing. For example, limits entering with a price 10 ticks away from the best price, have execution probabilities close to $\frac{1}{4}$. We also show that limit orders placed closer to the front of the book tend to be larger. These results extend similar analysis in Harris and Hasbrouck (1996) and Biais, Hillion, and Spatt (1995).

We proceed to investigate the own–and cross–dependence in arrivals of liquidity supply and demand events. To this end we construct a set of one–step and multi–step Markov transition matrices that give conditional event arrival probabilities. In this case, subsequent to the arrival of a market buy (sell) the supply of fresh liquidity at the front of the limit sell (buy) side of the order book tends to be reduced. This indicates some degree of *dynamic illiquidity*, in the sense that liquidity drained by trading activity is not immediately resupplied on the same terms, and is similar to the result, contained in Hasbrouck (1999), that NYSE market and limit order arrival intensities are negatively correlated at very high frequencies. Further event–time results show that liquidity supply temporally clusters on one side of the market and removal of liquidity at the front of one side of the book implies increased probability of seeing fresh liquidity at the front of the book and lower chances of seeing subsidiary liquidity supply on that side of the book.[2] These effects are persistent, being felt at least over 10 events into the future.

Subsequently, we model order arrival data in calendar time at a 20 second sampling frequency. We characterize the dependence of limit and market order entry rates on volatility,

[1] Harris and Hasbrouck (1996) also track limit order executions and compare implied costs with those of submitting market orders. Lo, Mackinlay, and Zhang (2001) provide empirical analysis of the likelihood of limit order executions using survival analysis.

[2] By subsidiary liquidity supply we mean submission of limit orders at prices inferior to the extant best limit price.

bid-ask spreads and extant order book depth. In a calendar–time setting, we obtain a result similar to several studies mentioned above, in that traders respond to low extant liquidity by supplying fresh liquidity. This result dovetails with our event-time result that subsequent to the removal of liquidity at the front of the book one is more likely to see fresh liquidity supplied at the front. We observe that limit and market order arrival rates increase with volatility. However, and in line with the theoretical predictions of Foucault (1999), the ratio of limit to market order arrivals also increases with volatility. Unlike previous authors, we demonstrate this result using order arrival data covering the entire limit order book.[3]

Finally, we estimate a joint dynamic model for spreads, depth, transaction activity and volatility.[4] Our depth measures are constructed as counts of the quantity of currency units available for trade at or within k ticks of the best extant limit price. We denote such a measure $d(k)_t^i$ where we allow k to vary between 0 and 10 ticks and $i = b, s$ for the limit buy and sell sides respectively. Thus, in contrast to many previous studies that have examined factors influencing measures of order book depth (Lee, Mucklow, and Ready 1993, Ahn, Bae, and Chan 2001, Brockman and Chung 1996, Kavajecz 1998), here depth is calculated from various points along the excess demand and supply curves implied by the order data rather than just at the best quotes. Our results indicate that, whilst rates of order submission in volatile and high volume intervals are increased, these new orders tend to be at poor prices such that order book spreads rise and depth is reduced. Further results break down activity by the side of the market. We show that market buy activity tends to reduce limit sell side depth but increases limit buy side depth, with corresponding effects following from market sell activity. Thus the response of buy and sell limit price schedules to transaction activity depends on both the amount and direction of the activity.

Overall, we attempt to provide a comprehensive empirical study of the liquidity of the

[3] A study using SEHK data on limit arrivals at the best prices only (Ahn, Bae, and Chan 2001) shows that arrival rates of these orders are increasing with volatility.

[4] A similar analysis focussing on spread determination only is contained in Bessembinder (1994). Ranaldo (2004) studies how transitory volatility affects order arrival rates, rather than order book depth.

D2000-2 segment of the USD/DEM market. The main messages of our results are as follows. Liquidity supply and demand exhibit clear self–regulating tendencies. When extant book liquidity is low, limit order entries increase relative to market order arrival. However, this picture is complicated by the responses of book liquidity variables to transaction activity and volatility. In our view, the responses of limit and market order arrivals, and thus spreads and depth, to transactions and volatility suggest an asymmetric information interpretation. We show that transaction activity increases subsequent volatility and reduces book liquidity, both spreads and depth — in response to potentially informed trades, limit orders are re-priced and the order book thins out as liquidity suppliers guard against being picked off by traders with superior information.

Finally, the fact that subsequent to market buy activity we observe a decrease in limit sell side depth and an increase in limit buy depth strengthens our belief that trades are providing information on the likely future direction of exchange rate changes. Corroborating evidence for the existence of asymmetric information in FX markets can be found in the literature linking currency order flows to exchange rate changes. Payne (2003) demonstrates that D2000-2 trades have permanent impacts on exchange rates using the same data that we employ here. Evans and Lyons (2001) demonstrate that a strong relationship between FX order flow and exchange rates is still found at the daily level, lending further credence to the asymmetric information hypothesis.

A final general observation from our analysis is that there is clear inter–dependence of volatility, transaction activity and liquidity. Transaction activity, for example, leads to higher volatility and lower liquidity and, in turn, high volatility and low liquidity tend to reinforce one another — a vicious liquidity/volatility cycle. From a policy perspective, the extent to which liquidity determination might prolong and exacerbate the effects of shocks on markets is an important question. Analysis similar to ours on a lower frequency level using data with a larger time–series dimension might shed light on how liquidity crises and extreme events in financial markets come about.

The rest of the paper is structured as follows. In the next section we give a description of the trading venue under analysis and the basic features of the data set derived from it. We also present our first analysis of the features of the liquidity supply process. In Section 2 we report results on conditional order event probabilities and our calendar time analysis of order arrival rates. Section 3 contains our analysis of the determination of order book depth. Section 4 concludes.

1 The Data and Basic Statistical Information

1.1 The Data Set

The data employed in this study are drawn from the D2000–2 electronic FX broking system run by Thomson Reuters. D2000–2 is one of the two main electronic brokers in this market, the other being EBS. Since the 1990s these venues have become increasingly important in inter-dealer FX trade. A figure of 15% represents a rough estimate of the portion of total inter-dealer trade in USD/DEM handled by D2000–2 at the time our sample was taken.[5]

The fact that D2000-2 is only one of the electronic brokers operating in the FX market and that we have no information on direct inter-dealer trade or on customer-dealer activity clearly implies that we cannot provide a picture of overall FX market liquidity. Rather, we characterise the order submissions to a particular trading venue in isolation and demonstrate the implications of these submissions for the co-determination of liquidity, volatility and transaction activity on that venue.

D2000–2 operates as a pure limit order market governed by rules of price and time priority.[6] At the time our data was recorded, the D2000–2 screen displayed to users the best

[5]This figure is derived from the tri-annual BIS reports on foreign exchange market activity which details the amounts of trade which are brokered versus direct and also on estimates of D2000–2 and EBS penetration in the brokered inter-dealer market.

[6]There is an exception to these rules driven by credit relationships between D2000–2 participants.

limit buy and sell prices, plus quantities available at those prices and a record of recent transaction activity, all for up to six currency pairs. It is important to note that, unlike many order driven trading systems in equity markets, information on limit buy (sell) orders with prices below (above) the current best price were not disseminated to users. Hence, and importantly for interpreting what follows, order book depth is not observable to D2000–2 users. Another difference between D2000–2 and other venues, is that at the time our sample was taken D2000–2 market orders were not allowed to "walk up the book". If the size at the extant best limit sell price, for example, was smaller than the quantity required in an incoming market buy, the market order filled the quantity available at the best quote and the excess quantity went unfilled. To the extent that limit order submitters do not monitor their order status on an event-by-event basis, and given that market order traders may input a sequence of orders that effectively "walk the book", we conjecture that, in practice, D2000–2 operates much like other order books where market orders can "walk the book".[7] See Danielsson and Payne (2002) for more detail on the operation of D2000–2 and the processing of this data set. As mentioned earlier, Lo and Sapp (2008) also study the data under analysis here.

Our data set contains order level information on all D2000–2 activity in USD/DEM from the trading week covering the 6th to the 10th of October 1997. The entry and exit times of every limit order submitted to D2000–2, plus the timing of every D2000–2 market order are recorded to the one hundredth of a second. As such, we can not only use the data to reconstruct all information displayed to market participants over our trading week, we can also see what happened to every limit order submitted to D2000–2, regardless of whether the order was traded or ever displayed to the public. Hence, we can measure the depth of the D2000–2 order book exactly, through reconstructing the excess demand and supply

D2000–2 participants must have bilaterally agreed credit relationships if they are to trade together. This means that, at some times, some banks may find the most competitive market prices unavailable. As such, the results derived in this paper should be interpreted from the perspective of an institution with a full set of credit agreements.

[7] Under the conditions we have laid out, subsidiary limit orders are still subject to the risk of being picked off by informed traders, for example.

curves for currency implied by the limit order data. As mentioned above, at the time, D2000–2 users got no information on depth outside the best quotes.

Table 1 gives summary information on the frequencies, prices, quantities and fill rates for each order type. Overall, around 130,000 orders were submitted during the sample period with approximately five times as many limit than market orders. Given that all orders must be for an integer number of \$m., the average limit order is relatively small at just over \$2m. The average market order is somewhat larger at \$3m., although still relatively small. Finally, just over one third of limit orders are totally filled while around 60% are not filled at all. About 65% of market orders fill totally with the remainder partially filled.

Table 2 gives information on the level of activity on D2000–2 and a first look at liquidity. It presents mean bid-ask spreads and transaction activity measures from a 20 second sampling of the data. The smallest price increment for USD/DEM on D2000–2 is one-hundredth of a Pfennig and, from now on, we refer to this increment as one tick. The mean spread from the 20 second data is 2.5 ticks indicating that, at first glance, D2000–2 is a very tight market.[8] Indeed, the modal spread in the data is 1 tick. In the average 20 second period there are between 3 and 4 transactions in USD/DEM with volume totalling \$6.15m.

To provide a more detailed (unconditional) picture of D2000–2 liquidity, in Table 3 we give basic statistical information on depth measures derived from the limit buy side of the order book.[9] The depth measure we employ is the total quantity in the book at prices at or within k ticks of the best extant limit price. Again, we generate these data on a 20 second calendar time sampling and denote them with $d_t^s(k)$ for the limit sell side and $d_t^b(k)$ for the limit buy side. We record data for $k = 2, 4, 6, 8$ and 10 ticks. We also record the quantity available at the best limit prices, denoting these with $d_t^s(0)$ and $d_t^b(0)$ respectively.

Table 3 indicates that the average depth at the best limit buy price, just over \$3m., is only just enough to satisfy one average size market order. Then, there is on average \$6m. on

[8] This figure of 2.5 ticks corresponds to a percentage spread of around 0.01%.

[9] Similar results for the limit sell side are omitted to conserve space.

offer across the two ticks immediately below the best price. From here, each increment of two ticks in limit price adds approximately \$4m. to depth such that the depth across the limit orders at or within 10 ticks of the best price is between \$24m. and \$25m. The table also demonstrates that, as one would expect, the depth measures for larger k are more strongly autocorrelated than those for small k. Hence, the picture of the order book which emerges is that depth appears to cluster just behind the best limit price but is also significant at prices up to 10 ticks away from the touch.

Finally, in Figures 1 and 2 we use the 20 second data sampling to construct the intra-daily patterns apparent in variables derived from D2000–2. In constructing these plots we omit data recorded between 16 GMT and 6 GMT due to very light activity in the GMT overnight period.[10] Figure 1 demonstrates that D2000–2 trading volume displays an approximate M-shaped pattern over the trading day, with local maxima at around 8 and 13 GMT. The second panel of this figure shows that D2000–2 inside spreads follow the opposite pattern, a W-shape. Spreads tend to be lowest between 8 and 10 GMT and 12 and 14 GMT. Figure 2 plots the intra-day activity patterns for limit buy depth measures with $k = 0$ and 4 ticks. It can be seen that, over the course of the trading day, depth follows a fairly similar pattern to trading volume and, as one would expect, the inverse pattern to the bid-ask spread. Hence, as measured by both spreads and depth, D2000–2 is most liquid in the periods from 8 to 10 and 12 to 14 GMT, when trading activity is most intense. The inverse relationship between spreads and depth measures is in line with results from Lee, Mucklow, and Ready (1993), Biais, Hillion, and Spatt (1995) and Ahn, Bae, and Chan (2001).

1.2 D2000–2 Order Placement

To give a first insight into the process through which liquidity is supplied to D2000–2, in this section we provide basic information on the properties of the limit orders submitted.

[10] From here on, we refer to the period between 6 GMT and 16 GMT as the trading day. For more detailed information on the basic activity patterns on D2000–2, see Danielsson and Payne (2002).

We begin by breaking down the limit orders by the position at which they entered the order book. We do this in two ways. First, we count the total quantity in \$m. ahead of the incoming order in the execution queue. Second, we assign each incoming order a price position. If the incoming order is a limit buy then its price position is its price less the extant best limit buy price. If the incoming order is a limit sell then the price position is the extant best sell price less the incoming limit price. As such, all orders with positive price positions improve the prior best limit price.[11] Based on this breakdown of limit orders we examine four order characteristics; entry probability, fill probability, average lifetime and average size. The results of these breakdowns are given in Figures 3 and 4.

Figure 3 gives information based on the quantity position of orders. The first panel of the figure demonstrates that by far the most common position for order entry is at the front of the execution queue (i.e. a quantity position of zero). Just over 30% of all orders improve upon the best available price in the book. Entry probability declines fairly monotonically with quantity position and, for all positions greater than zero, entry probability is lower than 0.1. Panel (b) presents the obvious result that orders placed at the front of the book are most likely to execute. However, interestingly, it also shows that orders a long way down in the execution queue have fairly good chances of execution. On average, for example, an order with \$10m. ahead of it in the queue still has a 30% probability of execution. Hence, the expected price improvement from such a limit order is clearly non-negligible. Panel (c) demonstrates that limit order lifetimes increase fairly monotonically with quantity position. Finally, panel (d) shows that those orders entered at the front of the book are for larger quantities on average.

Figure 4 gives similar results based on the price position of an order at entry. Arguably, the results based on price position are more relevant if we wish to understand the order

[11] To clarify this procedure, consider the following example. A limit sell enters with price 1.7505. If there are two orders on the book at 1.7502, three at 1.7504, 1 at 1.7505 and 5 at 1.7507 then the incoming order moves to position seven in the execution queue via price and time priority. The price position of the new order is -3 ticks. The total quantity ahead of the new order is the sum of the individual quantities for existing orders at 1.7502, 1.7504 and 1.7505.

placement decisions of D2000–2 users. This is because a user can control price position of an order exactly, whilst in the majority of cases the quantity position of an order will be unknown. From Figure 4 we see that entry probability is most common at the best extant limit price (around 30% of orders enter here.) Approximately 20% of orders improve the best price by 1 tick and just over 5% of orders improve the extant best price by 2 ticks. Also, over 10% of orders enter at prices 1 tick worse than the best limit price. Hence, the majority of D2000–2 order placement occurs at or within 1 tick of the best price. This result conforms with that based on data from the Paris Bourse in Biais, Hillion, and Spatt (1995). From Figure 4 we again see that transaction probability increases as the order is positioned closer to the front of the execution queue and that average order lifetime decreases as price position improves. Again, panel (b) demonstrates that execution probabilities for orders a fair way down the execution queue are far from trivial. Finally, the fourth panel of the Figure gives further evidence that larger orders are placed closer to the front of the book.

Hence, the preceding analysis demonstrates the existence of clear patterns in the order placement decisions of D2000–2 users. D2000–2 liquidity supply is concentrated at the front of the order book, in a range from 2 ticks below to 2 ticks above the extant best limit price. A fair amount of limit order flow improving prices by one or two ticks is to be expected at times when revelation of information implies current best prices can be bettered. Concentration of liquidity supply just below the best limit price may exist to make money from uninformed market order traders desiring to deal relatively large amounts.

2 Analysis of D2000–2 order flows

Our first set of econometric exercises concentrates on identifying the determinants of and relationship between limit order and market order placement. As such, we hope to shed some light on the dynamics of the D2000-2 liquidity supply and demand processes as discussed in the Introduction. On a more practical level, this analysis will reveal how traders' order submission strategies vary with observable market events.

We begin by looking at an event-time data set of order placements and constructing measures of serial and cross dependence for the different types of order arrival. From this analysis we can empirically evaluate predictions regarding conditional probabilities of order placements contained in Parlour (1998). We then proceed to study a calendar time data set (using a 20 second sampling frequency) which allows us to model the rates of limit and market order arrival. Using these data we can examine the relationship between limit/market order placements and price movements discussed in Foucault (1999).

2.1 Event-time dependence in order arrival

To begin, we attempt to characterise how and when liquidity is supplied to D2000–2 and when liquidity is drained from D2000–2 in terms of the recent history of supply/demand events. To accomplish this task we work with an event-time filtration of the D2000–2 data. This data set places each D2000–2 order event into one of 10 categories. These categories are; market buy; market sell; subsidiary limit buy entry; new best limit buy or fresh liquidity at best limit buy; subsidiary limit sell entry; new best limit sell or fresh liquidity at best limit sell; cancellation of subsidiary limit buy; removal of liquidity at best limit buy price; cancellation of subsidiary limit sell; removal of liquidity at best limit sell price. It is important to note that only six of these ten event types are observable to D2000–2 users. All actions involving subsidiary limit orders are invisible to all D2000-2 participants aside from the agent actually adding or cancelling the order.

We investigate the dependencies in the event-level data through the construction of a number of transition matrices. The typical element of such a matrix gives the conditional probability of observing event type i in k events time, given that one has just observed an event of type j. We present results for k equals one and five so as to emphasise the immediate impacts of certain events whilst also providing information on the persistence of these effects. Finally, it should also be noted that we only compute probabilities conditional on the group of 6 order events that are observable to D2000–2 users.[12]

The one and five-step ahead transition matrices are given in Table 4. The first row of the table gives the unconditional probability of observing the event named in the column head and the remaining rows give probabilities conditional on having observed the event named in the row head.

A number of interesting results emerge upon examination of panel (a) of Table 4. First, there is evidence of positive dependence in all event types represented. The probabilities of market buys/sells conditional on just having observed a market buy/sell are over twice the corresponding unconditional probabilities. A similar observation is true for events based on liquidity removal at the best prices and, to a somewhat smaller extent, for fresh liquidity supply at the front of the order book. The positive dependence in market order arrival might be due to information-based trade generating imbalances in liquidity demand or due to traders wishing a deal a large amount having to repeatedly place small market orders. Positive dependence in liquidity supply at the front of the book is in line with results in Biais, Hillion, and Spatt (1995). The dependence in liquidity removal at the front of the book may be due to traders sequentially removing mis-priced orders after the revelation of public information or after informative trading activity.

Panel (a) of Table 4 also reveals a number of interesting effects of market orders on conditional limit order arrival probabilities. Arrival of a market buy (sell) at event date t reduces the probability of observing new best limit sell (buy) liquidity at $t+1$. Conversely, subsequent to a market buy (sell), the chances of seeing new limit buy (sell) liquidity at the front of the book are greatly increased. The fact that market order activity inhibits subsequent liquidity supply at the front of the opposite side of the order book may be generated by concerns regarding asymmetric information in the hands of market order traders. Liq-

[12] Also, we performed some analysis to investigate the stability of the transition matrices across the trading day. This analysis indicated that time-of-day variation in the conditional probabilities was minor.

uidity suppliers are not (or are less) willing to replace liquidity drained through market order activity at the same price if they believe that market orders convey information. In the Introduction, we labelled this phenomenon *dynamic illiquidity*. The effect of market buys (sells) on subsequent best limit buy (sell) entry is also consistent with asymmetric information, in that potentially information revealing buys (sells) lead limit order traders to revise opinions of fair limit buy (sell) prices upwards (downwards).

Finally, the entry and removal of liquidity supply at the best price also have some interesting implications. After liquidity supply at the front of the book there are increased chances of seeing fresh liquidity supply on the same side of the book. Hence traders follow new best prices by supplying extra liquidity behind them (or extra size at the best prices). After observing the removal of liquidity at the best price one is more likely to see that liquidity replaced and less likely to see subsidiary supply on the same side of the book.

The 5-step ahead transition matrix in panel (b) of Table 4 demonstrates that the effects of market orders are most persistent over time. Dependence in market order direction is still clearly visible in the table as are the effects of market orders on later liquidity supply decisions. Thus, it would seem that market order activity (i.e. aggressive order placement) has the most long-lasting effects on order book events.

Finally, it is interesting to compare our results to the theoretical predictions regarding order placement probabilities contained in Parlour (1998). Parlour postulates an order driven market where order live for multiple periods but no limit price variation is permitted. The market is assumed to have symmetric information and traders are distinguished by their degree of patience. Further, traders are exogenously designated as either buyers or sellers. Hence, the basic tradeoff faced by those submitting orders is the cost of market orders versus the execution risk of limit orders. The first result derived is that market order direction is positively autocorrelated. Further, the probability of a limit buy (sell) is lowest if the immediately preceding event was also a limit buy (sell). Finally, the probability of a limit buy (sell) is shown to be maximised after the occurrence of a market sell (buy).

Clearly, only the theoretical prediction regarding serial correlation in market order direction matches our results. In our data, the other two theoretical results are soundly rejected. We show that limit buys are less common than unconditionally after market sells and that the probability of a limit buy after having already observed a limit buy is fairly high. We have argued that asymmetric information might explain these results, an effect which is missing from the analysis of Parlour (1998). Payne (2003) uses the technology developed in Hasbrouck (1991a) and Hasbrouck (1991b) to demonstrate that market orders in the sample of data studied in the current paper do carry information relevant for exchange rate determination. This may help to explain why Parlour's predictions do not hold in our analysis. It further suggests that models of order driven markets that allow optimal choice of order type and feature asymmetric information, for example Handa, Schwartz, and Tiwari (2003) and Goettler, Parlour, and Rajan (2009), may be more appropriate representations of trade on D2000-2.

2.2 Explaining order arrival rates

In this section we focus on evaluating theoretical predictions regarding the effect of price movements on limit and market order *flows* and also on the composition of overall order flow. Further, we empirically relate order flows to prior indicators of book liquidity observable to market participants.

To accomplish this task, we construct a data set sampled every 20 seconds from the original event time data. For each 20 second interval we record the following variables; the total number of limit orders submitted; the number of market orders submitted; the net number of limit orders submitted (i.e. the number actually submitted less the number cancelled or removed); midquote return volatility; the end-of-interval bid-ask spread; and end of interval size at the best limit prices .[13]

[13]The midquote is the average of the best, end-of interval bid and ask quotes. The midquote return is the percentage change in this measure from start to end of interval. Volatility is measured as the absolute return.

The questions addressed in this section are partially motivated by the work of Foucault (1999), who provides a dynamic model of order placement with variation in asset valuation across agents. The model permits differences in limit prices but restricts limit orders to last for one trading round only. The basic theoretical feature of the model is a Winner's Curse problem for limit order traders. The key empirical prediction from Foucault's analysis is that the proportion of limit orders in total order flow is increasing in return volatility. This is driven by the fact that, with increased volatility, limit orders are placed at less competitive prices. Due to this, market order submission becomes less profitable.

To examine this prediction we regress order entry rates over the interval from $t-1$ to t on volatility measured as the absolute return over the interval ending at $t-1$.[14] Denoting the variable to be explained with z_t, we run the following linear regression;

$$z_t = \alpha|R_{t-1}| + \sum_{i=1}^{10} \beta_i z_{t-i} + \varepsilon_t \tag{1}$$

where ε_t is a regression residual. We include 10 lags of the dependent variable on the right-hand side of the regression to pick up any own-dependence in arrival rates. A further point to be noted is that, prior to running regressions of the form in (1), we remove the repeated intra-day patterns from all variables involved. This is done so as to ensure that the results derived are not simply due to predictable market activity variation affecting liquidity and volatility variables in similar ways.[15]

Results from the relevant regressions are given in the first panel of Table 5. The table shows that lagged volatility has a significant and positive effect on both limit and market order entry frequency. Moreover, volatility increases subsequent *net* limit order arrivals —

Our size variable is the sum of quantity available at the best limit buy price and quantity available at the best limit sell price.

[14]We use lagged volatility as the explanatory variable to avoid picking up a mechanical relationship between order entries and volatility.

[15]To remove the intra-day patterns we scale each observation by the mean value of all observations taken at that time of day across all days.

faced with price uncertainty the rate at which limit order traders supply liquidity relative to the rate at which liquidity is removed increases. Examination of the final row of this panel also shows that the proportion of limit orders in total order flow increases with volatility. Hence, in line with the contribution of Foucault (1999), greater uncertainty regarding prices translates to less competitive limit prices and this curtails market order placement.

To complement this analysis, in panels 2 and 3 of Table 5 we regress order entry rates on prior measures of liquidity observable to D2000–2 users — bid-ask spreads and size at the best quotes. This regression analysis delivers the nice result that when there are indications of low D2000–2 liquidity, traders tend to supply liquidity via limit orders and, when D2000–2 liquidity is seen to be high, liquidity tends to be demanded. Hence, there appear to be clear self-regulating tendencies in D2000–2 liquidity. A result with a very similar flavour is presented in Hall and Hautsch (2007). It should be noted, though, that our limit order flow variables do not incorporate price information such that we cannot argue that in times of high spreads or low size at the best quotes, the orders entering tend to reduce spreads or increase size.

One might object that the relationship between order flows and observable liquidity indicators are in fact driven by the relationship between volatility and order entries, given that spreads and size are likely to be strongly contemporaneously correlated with volatility. To address such an objection, in the final panel of the table we regress order entry rates on all three variables. In the majority of cases the right-hand side variables retain their significance such that volatility and observable liquidity measures have independent roles to play in explaining subsequent liquidity supply and demand. However, the effect of volatility on the share of limit orders in total order flow now becomes insignificant: it would appear that the composition of D2000–2 order flow is better explained by the prior state of the book rather than prior volatility in the best limit prices.

To summarise, we have derived calendar-time results which complement the event-time analysis of Section 2.1. We show that one can predict liquidity supply and demand based on the sequence of recent order events, but also that one can use liquidity *snapshot* variables plus volatility to explain subsequent rates of liquidity supply and demand.

3 Analysis of D2000–2 depth

The analysis of Section 2 focussed on the arrivals of limit and market orders to D2000–2 but largely ignored the price and quantity information from incoming limit orders. We now re-involve the price and quantity information and investigate the implications of order arrivals (and removals) for the *slopes of the excess demand and supply curves* implied by the D2000–2 data — i.e. we examine the determination of D2000–2 depth. Based on the analysis of previous sections we attempt to explain depth in terms of three factors; market order activity (the sum of market buy volume and market sell volume, denoted V_t), midquote return volatility ($|R_t|$) and spreads (S_t). The depth variables we employ, introduced in Section 1, measure the slope of the excess demand and supply curves from the front of the order book to a point k ticks into the order book for k between zero and ten ticks. As in Section 2.2, all of the variables used in this analysis are sampled every 20 seconds and have had deterministic intra-day patterns removed.

Prior to our examination of depth determination, in Table 6 we present correlations between depth measures from the buy and sell sides of the order book. This table highlights an interesting result. After accounting for the intra-day patterns in the data, there is essentially no correlation between depth measures on different sides of the book. Hence the quantities available at and around the best bid and ask appear to evolve separately. This implies that D2000–2 liquidity suppliers tend not to mechanically post orders on both sides of the market in the style of a traditional market-maker. Rather, they appear to focus on one side of the market at a given point in time.

3.1 Depth, spreads, volume and volatility

As noted earlier, the vast majority of academic empirical work on determination of market liquidity looks at bid-ask spreads. Our final piece of analysis extends this research to include investigation the determinants of order book depth.

We employ a general dynamic model for this investigation, adapted to account for the the fact that depth is not observable to D2000–2 users. The basis of the empirical model is a sixth order VAR in total market order volume, midquote return volatility and bid-ask spreads.[16] This VAR is not entirely standard, though, as we allow volume to contemporaneously affect both volatility and spreads and also allow volatility to contemporaneously influence spreads. This causal ordering identifies the VAR. The final piece of the empirical model is a depth equation, where our depth variable is the sum of buy and sell side depth for a given value of k (i.e. the depth measure is $d_t^b(k)+d_t^s(k)$). We regress depth on exactly the same variables that appear on the right-hand side of the spread equation (i.e. current and lagged volume, current and lagged volatility and lagged spreads). Note that depth does not appear on the right-hand side of any equation. Note also that in running this depth regression for several values of k we can investigate how volume, volatility and spreads affect depth close to and further away from the best prices.

The motivation for our model specification is an attempt to capture the dynamic interactions between the four variables under examination while imposing some theory and microstructure-based restrictions. Hence, depth does not appear on the right-hand side of any equation as it is not observable to D2000–2 users. In the three-variable VAR involving volume, volatility and spreads, the causal ordering is driven by the fact that, in most microstructure models, trading activity is the driving variable, which subsequently affects volatility and both volume and volatility then influence trading costs. However, it should be noted that our results are robust to sensible reorderings of the three variables. The

[16] The results we present are not at all sensitive to the choice of VAR order. A sixth order VAR was indicated by the Schwartz Information criterion.

equations we estimate for spreads and depth are similar to those that Bessembinder (1994) specifies for determination of FX spreads, in that we attempt to explain determination of liquidity variables in terms of prior trading volumes and return volatility. Coppejans, Domowitz, and Madhavan (2004) also estimate VAR models including volatility and measures of liquidity in their microstructure analysis of the Swedish stock index futures market.

Results from the estimation of this empirical specification are given in Tables 7 and 8. The first of these tables gives results from the VAR estimation in volume, volatility and spreads and the latter gives estimates from the depth equation for $k = 2, 6, 10$.[17] Looking first at Table 7 one sees that all three variables are strongly positively autocorrelated. There is strong evidence that market order volume leads immediately to increased volatility and spreads. Increased volatility leads to significantly increased market order volume and also significantly larger spreads.[18] Finally, larger spreads are associated with lower subsequent trading activity and higher volatility. All of these effects are apparent not only via the t-values for individual right-hand side variables but also from the χ^2 statistics in the final rows of the table which are test statistics for the null that coefficients on all included volume, volatility or spread variables are simultaneously zero. The explanatory power of all three equations is relatively good.

Examination of the estimated coefficients from the depth regressions, presented in Table 8, provides a number of interesting, new results. There is unambiguous evidence that increased volatility leads to decreased depth. A similar result is reported in the previously mentioned work by Coppejans, Domowitz, and Madhavan (2004). Further, increased spreads are associated with significantly lower subsequent depth. Hence, in times of large price variation those supplying liquidity do so on worse terms and this is reflected in both higher spreads and lower depth. Such a result is consistent with the intuition delivered by a model of liquidity supply based on asymmetric information, as are the results from the VAR estimates. Intuition from a simple asymmetric information model would predict a

[17] It should be noted that all of our inference is based on Newey-West robust standard errors.

[18] A similar result to the latter is contained in Bollerslev and Melvin (1994).

positive relationship between volume and volatility plus a negative relationship between volatility and subsequent measures of liquidity. The latter relationship could also be driven by risk-aversion on the part of liquidity suppliers.

A more complicated relationship is that between trading volume and depth. Table 8 shows that increased volume tends to immediately decrease depth, as one might expect, but then leads to significantly larger depth. This final result would appear to be at odds with any explanation of the inter-relationships between the four variables that is based on private information in the hands of market order traders or risk-aversion.

However, if one considers the implications of an asymmetric information story more carefully then a complicating factor becomes apparent. One would expect market buys and market sells to have non-symmetric effects on limit buy and sell side depth. Specifically, arrival of a market buy order would signal to liquidity suppliers that the informed market traders have observed news implying that quotes should be higher — a good private signal . A likely response to this is that depth on the limit sell side of the market would be reduced. However, simultaneously one would expect depth on the limit buy side of the market to rise as limit buyers revise downwards their probabilities of the existence of a bad private signal.

Hence, to test this implication, we re-estimate the empirical model with separate equations for market buy volume, market sell volume, limit buy depth and limit sell depth. The results from the market buy volume, market sell volume, volatility and spread equations respectively are similar to those for the total volume, volatility and spreads in Table 7 and hence we omit them to save space.[19]

The results from the separate buy and sell side depth equations are contained in Table 9. Again we observe strong evidence that high volatility and large spreads lead to decreases in order book depth, both buy and sell side. However, the separation of market buy and sell

[19] The only new result here is that market buy and sell volume are effectively unrelated i.e. lagged market buy activity does not affect current market sell activity and vice versa.

volume clarifies the influence of market order activity on depth. We see that limit buy side depth, for example, tends to be negatively affected by market sell activity and positively influenced by market buy activity. A symmetric result holds for limit sell side depth and the significance of these results is greater for depth measures covering a larger number of ticks. These results are entirely consistent with the asymmetric information story outlined above and consistent with the finding, in Payne (2003), that D2000-2 order flow carries information.. Further, it is difficult to see how such results could be generated by inventory concerns of limit order traders. The fact that both limit buy and sell curves shift in response to trades on a single, given side of the market is tough to understand if all that matters for depth determination is the distribution of inventory positions across limit order traders.

Finally, these results are consistent with those described in Section 2. There we showed that market buy activity leads to a decreased probability of subsequently seeing aggressively priced limit sells whilst the converse was true for the probability of seeing aggressively priced limit buys. Also, we showed that volatility leads subsequently to increased shares of limit orders in overall order flow. We argued that this was due to the fact that the limit orders were repriced to imply poorer execution for market orders. Our depth results confirm this argument — volatility leads to larger spreads and lower depth.

4 Conclusion

This paper presents a comprehensive examination of liquidity determination on an order-driven FX broking system. We look not only at standard measures of liquidity based on bid-ask spreads and trading activity, but also use the complete order level data available to us to study measures based on order arrival rates (and probabilities) and to examine the determination of order book depth. Our depth measures are based on the slopes of the excess demand and supply curves implied by the limit buy and sell orders. Our study was the first, to our knowledge, to look at such slope-based depth measures rather than simple measures of quantity available at the inside quotes.

A number of interesting results emerge from our analysis. Via event-time transition analysis, we demonstrate that market order activity has strong and relatively persistent effects on subsequent limit order placement. Market buy activity, for example, reduces the likelihood of observing the entry of limit sells orders at the front of the order book. Conversely, after market buy activity one is more likely to observe the placement of limit orders at the front of the buy side of the book.

A calendar time analysis of order arrival rates shows that both limit order and market order arrivals increase in volatile periods. In line with the theoretical results of Foucault (1999), we also provide evidence that the share of limits in total order flow tends to increase with volatility. Further, we demonstrate that when order book liquidity is visibly low (high), limit order entries are more (less) frequent and market order arrivals less (more) frequent.

Our final set of empirical exercises focusses on the determination of limit order book depth. We demonstrate that the magnitudes of the slopes of the excess demand and supply curves implied by outstanding limit orders increase in volatile periods and in periods of high spreads. Thus liquidity as measured by spreads and depth move in the same direction and both liquidity measures are eroded in times of high volatility. It is likely that this liquidity erosion in volatile times underlies the preceding result whereby volatility increases the share of limit orders in overall order flow — the liquidity reduction makes market orders less attractive. Depth is also related to trading activity. After market buy activity, one sees the slope of the excess demand curve decrease (buy side depth increases) and the slope of the excess supply curve rises (sell side depth is reduced).

We believe that these results are indicative of information asymmetries in inter-dealer FX markets, with the asymmetric information in the hands of market order traders. In such a setting, one would expect trading volume to increase volatility (through the incorporation of information into prices) and one would then expect to see reduced liquidity. Aggressive buy orders would likely signal to liquidity suppliers that prices will rise in future and hence they re-price limit orders upward leading to reduction in limit sell side depth. Similarly upwards re-pricing of limit buy orders will increase buy side depth. On an order-by-order level, asymmetric information will lead to market buys inhibiting subsequent limit sell orders at good prices, exactly as we see in the data. Corroborating evidence for our information based view can be found in the literature which examines the relationship between FX order flows and exchange rates (Evans and Lyons 2001, Payne 2003).

A final feature of our results is the dynamic interaction between volume, volatility and liquidity variables. In particular, we see that liquidity and volatility are negatively related. This observation squares with much casual empiricism conducted regarding the recent financial crisis as it suggests that the reaction of market liquidity to price shocks may exacerbate and perpetuate price fluctuations. Thus, the behaviour of liquidity can help explain high levels of and persistence in intra-day financial return volatility and may contribute to the observation of extreme return events.

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Table 1: Basic Summary Statistics by Order type

Order type	Number	$\bar{P}$	$\bar{Q}$	Q_{25}	Q_{75}	$\bar{D}$	Part. fill	Total fill
Limit Buy	55240	1.7512	2.09	1.00	2.00	0.68	0.036	0.339
Limit Sell	53408	1.7520	2.09	1.00	2.00	0.72	0.038	0.356
Market Buy	11128	1.7515	3.29	1.00	5.00	1.82	0.356	0.644
Market Sell	10655	1.7513	3.18	1.00	5.00	1.82	0.361	0.639

$\bar{P}$ is the average price of orders of a given type, $\bar{Q}$ is average requested quantity and Q_{25} and Q_{75} are the 25^{th} and 75^{th} percentiles of the quantity distribution. $\bar{D}$ is average traded quantity and the columns headed “Part. fill” and “Total fill” give the proportion of all orders which were partially or totally executed.

Table 2: Market Activity Statistics: 20 Second Data Sampling

Variable	Mean	s.d.	Q_{25}	Q_{50}	Q_{75}	$\hat{\rho}_1$
Spread	2.54	2.09	1	2	3	0.46
Trade frequency	3.35	3.70	1	2	5	0.51
Gross volume	6.15	7.56	1	4	8	0.43
Net volume	0.06	6.94	-2	0	2	0.18

Spread measurement is in ticks. Gross volume is the sum of market buy and sell volume in each interval. Net volume is the difference between market buy and market sell volume. The data are sampled every 20 seconds and only observations between 6 and 18 GMT are considered. The column headed s.d. gives standard deviations and the following three columns give the 25th, 50th and 75th percentiles of the empirical distributions. The final column gives the estimated autocorrelations at displacement one.

Table 3: Buy Side Depth Statistics: 20 second data

Variable	Mean	s.d.	Q_{25}	Q_{50}	Q_{75}	$\hat{\rho}_1$
$d_t^b(0)$	3.55	3.14	1	3	5	0.19
$d_t^b(2)$	9.08	6.33	4	8	12	0.55
$d_t^b(4)$	13.62	8.52	7	12	18	0.70
$d_t^b(6)$	17.61	10.17	10	16	23	0.76
$d_t^b(8)$	21.32	11.71	12	20	28	0.81
$d_t^b(10)$	24.47	12.83	15	23	32	0.84

$d_t^b(k)$ is the total quantity at limit prices at or within k ticks of the best limit price. The data are sampled every 20 seconds and only observations between 6 and 18 GMT are considered. The column headed s.d. gives standard deviations and the following three columns give the 25th, 50th and 75th percentiles of the depth distributions. The final column gives the estimated autocorrelations at displacement one.

Table 4: Transition Matrices for Order Data

	Market orders		Limit buy arrivals		Limit sell arrivals		Limit buy cancel		Limit sell cancel	
	Mkt. sell	Mkt. buy	New SLB	New BLB	New SLS	New BLS	Cut SLB	Cut BLB	Cut SLS	Cut BLS
Uncond.	0.0540	0.0565	0.1178	0.1571	0.1115	0.1556	0.1129	0.0656	0.1053	0.0638
(a) One-step transitions										
Mkt. sell	0.1135	0.0259	0.0987	0.1010	0.0881	0.2286	0.0730	0.0572	0.1295	0.0845
Mkt. buy	0.0243	0.1228	0.0974	0.2268	0.0866	0.1019	0.1358	0.0870	0.0675	0.0500
New BLB	0.0360	0.0722	0.1479	0.1739	0.0972	0.1326	0.1278	0.0702	0.0847	0.0575
New BLS	0.0708	0.0365	0.1003	0.1359	0.1448	0.1735	0.0890	0.0620	0.1217	0.0654
Cut BLB	0.0296	0.0560	0.0821	0.1941	0.1025	0.1596	0.1013	0.1140	0.0965	0.0641
Cut BLS	0.0559	0.0396	0.1144	0.1631	0.0795	0.1882	0.0993	0.0599	0.0916	0.1085
(b) Five-step transitions										
Mkt. sell	0.1010	0.0258	0.1153	0.1257	0.1025	0.1956	0.0747	0.0431	0.1375	0.0788
Mkt. buy	0.0267	0.0975	0.1025	0.1950	0.1106	0.1254	0.1467	0.0816	0.0698	0.0441
New BLB	0.0447	0.0685	0.1202	0.1690	0.1000	0.1354	0.1336	0.0889	0.0869	0.0528
New BLS	0.0636	0.0479	0.1053	0.1397	0.1155	0.1693	0.0930	0.0550	0.1253	0.0855
Cut BLB	0.0421	0.0548	0.1131	0.1787	0.1138	0.1676	0.1092	0.0675	0.0918	0.0614
Cut BLS	0.0551	0.0407	0.1228	0.1688	0.1023	0.1776	0.0998	0.0638	0.1011	0.0679

The first row of the table gives the unconditional probability of observing the event in the column head. The rest of the table gives the probability of observing the event in the column head subsequent to the event in the row head. Panel (a) gives one-step ahead probabilities and panel (b) five-step ahead probabilities. Probabilities may not sum to unity across rows due to rounding. The results are based on event-time data with all events outside 6 to 18 GMT omitted. SLB stands for subsidiary limit buy, BLB for best limit buy, SLS for subsidiary limit sell and BLS for best limit sell.

Table 5: Determination of order entry rates

Dep. Var.	Coefficients and t-statistics on RHS variables						
	$\lvert R_{t-1}\rvert$	t-stat	S_{t-1}	t-stat	D_{t-1}	t-stat	R^2
LO_t	147.43	17.90	-	-	-	-	0.54
MO_t	16.14	4.31	-	-	-	-	0.22
NLO_t	25.30	2.69	-	-	-	-	0.11
OR_t	0.63	4.28	-	-	-	-	0.98
LO_t	-	-	0.35	8.91	-	-	0.52
MO_t	-	-	-0.10	-7.89	-	-	0.22
NLO_t	-	-	0.27	8.96	-	-	0.12
OR_t	-	-	0.01	13.99	-	-	0.98
LO_t	-	-	-	-	0.006	0.40	0.52
MO_t	-	-	-	-	0.031	5.71	0.22
NLO_t	-	-	-	-	-0.075	-6.01	0.12
OR_t	-	-	-	-	-0.001	-2.64	0.98
LO_t	136.49	15.67	0.21	5.11	0.010	0.76	0.55
MO_t	21.02	5.60	-0.12	-8.63	0.031	5.69	0.23
NLO_t	17.09	1.75	0.25	7.93	-0.077	-6.29	0.13
OR_t	0.11	0.75	0.01	13.71	-0.001	-2.92	0.98

The table reports coefficients from regressions of the variables listed in the left-hand column on the variables listed in the heads of the remaining columns plus 10 lags of the dependent variable. All data is calendar time sampled at a 20 second frequency. t-values are heteroskedasticity robust. LO_t measures the numbers of limit orders entering in a given interval, MO_t measures the number of market order entering, NLO_t is the number of limit order entries less the number of limits removed and OR_t is the ratio of the number of limits entering to the total number of limits and markets entering. R_t is the midquote return, S_t is the bid-ask spread and $D_t = d(0)_t^b + d(0)_t^s$ is total size at the best quotes. All variables used in this analysis except NLO_t have had their repeated intra-day patterns removed prior to the analysis. All t-statistics are based on Newey-West heteroskedasticity and autocorrelation robust standard errors.

Table 6: Correlations between limit buy and sell depth measures

Variables	Correlation
$d_t^b(0)$, $d_t^a(0)$	0.01
$d_t^b(2)$, $d_t^a(2)$	0.06
$d_t^b(4)$, $d_t^a(4)$	0.01
$d_t^b(6)$, $d_t^a(6)$	-0.03
$d_t^b(8)$, $d_t^a(8)$	-0.01
$d_t^b(10)$, $d_t^a(10)$	-0.01

The table reports cross-correlations between limit buy-side and sell-side depth measures where $d_t^b(k)$ is the total quantity at limit prices at or within k ticks of the best limit buy and $d_t^a(k)$ is the total quantity at limit prices within k ticks of the best limit sell. The data used to construct these correlations is based on a 20 second calendar-time sampling and only observations between 6 and 18 GMT are employed. Prior to computing the correlations the repetitive intra-day pattern is filtered from all depth measures.

Table 7: VAR coefficients: volume, volatility and spreads

Regressor	Volume eqn.		Volatility eqn.		Spread eqn.	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
V_t	-	-	0.448	17.34	0.134	8.6
V_{t-1}	0.214	11.42	0.015	0.9	0.002	0.12
V_{t-2}	0.072	4.73	-0.015	-1.01	-0.054	-3.89
V_{t-3}	0.111	6.55	-0.048	-3.02	-0.037	-2.79
V_{t-4}	0.079	3.53	-0.014	-0.99	-0.025	-2.05
V_{t-5}	0.051	3.25	-0.019	-1.53	-0.035	-3.27
V_{t-6}	0.066	3.96	-0.003	-0.22	-0.037	-3.05
$\|R_t\|$	-	-	-	-	0.086	4.15
$\|R_{t-1}\|$	0.067	4.73	0.108	5.06	0.027	1.54
$\|R_{t-2}\|$	0.041	2.31	0.057	4.03	0.048	2.52
$\|R_{t-3}\|$	0.035	2.2	0.063	4.63	0.000	0.02
$\|R_{t-4}\|$	0.014	1.15	0.022	1.46	0.002	0.12
$\|R_{t-5}\|$	0.003	0.27	0.018	0.83	0.018	1.37
$\|R_{t-6}\|$	0.02	1.79	0.034	2.85	0.004	0.25
S_t	-	-	-	-	-	-
S_{t-1}	-0.101	-7.67	0.179	8.34	0.249	7.69
S_{t-2}	0.02	1.56	-0.025	-1.77	0.136	7.14
S_{t-3}	-0.019	-1.69	-0.006	-0.46	0.063	2.85
S_{t-4}	0.005	0.41	-0.013	-1.08	-0.003	-0.16
S_{t-5}	0.027	2.12	0.033	2.18	0.059	3.46
S_{t-6}	-0.005	-0.49	0.009	0.74	0.079	4.71
R^2	-	0.23	-	0.32	-	0.23
Volume	-	643.1	-	466.51	-	148.81
Volatility	-	47.47	-	130.89	-	38.39
Spread	-	73.27	-	89.05	-	220.77

The table reports coefficients from a 6-lag VAR involving trading volume, absolute returns and spreads. V_t is defined as the sum of market buy and market sell volume in a given interval. The data upon which the VAR is estimated is sampled on a 20 second calendar-time basis and only observations between 6 and 18 GMT are employed. Prior to estimation the repetitive intra-day pattern is filtered from all variables. All t-statistics and χ^2-statistics are based on Newey-West heteroskedasticity and autocorrelation robust standard errors.

Table 8: Regressions of depth measures on volume, volatility and spreads

Regressor	2-tick depth eqn. Coeff.	t-value	6 tick depth eqn. Coeff.	t-value	10 tick depth eqn. Coeff.	t-value
V_t	-0.049	-3.34	-0.073	-5.61	-0.074	-6.15
V_{t-1}	0.043	3.29	0.050	4.23	0.031	2.79
V_{t-2}	0.053	3.94	0.056	4.83	0.050	4.27
V_{t-3}	0.071	5.79	0.070	6.58	0.060	5.25
V_{t-4}	0.034	2.79	0.058	5.16	0.048	4.34
V_{t-5}	0.014	1.06	0.044	3.56	0.044	3.76
V_{t-6}	0.032	2.51	0.042	3.14	0.046	3.48
$\|R_t\|$	-0.085	-5.54	-0.115	-8.03	-0.114	-8.90
$\|R_{t-1}\|$	-0.082	-6.27	-0.082	-6.50	-0.074	-6.48
$\|R_{t-2}\|$	-0.059	-4.82	-0.066	-5.12	-0.059	-4.95
$\|R_{t-3}\|$	-0.054	-4.85	-0.051	-4.78	-0.049	-4.66
$\|R_{t-4}\|$	-0.024	-2.12	-0.038	-3.41	-0.036	-3.43
$\|R_{t-5}\|$	-0.038	-3.24	-0.046	-3.94	-0.043	-3.86
$\|R_{t-6}\|$	-0.046	-4.08	-0.052	-4.69	-0.048	-4.44
S_t	-	-	-	-	-	-
S_{t-1}	-0.059	-4.7	-0.069	-5.55	-0.068	-5.49
S_{t-2}	-0.044	-4.04	-0.036	-3.43	-0.045	-4.17
S_{t-3}	-0.028	-2.69	-0.038	-4.04	-0.045	-4.67
S_{t-4}	-0.005	-0.47	-0.020	-2.22	-0.031	-3.14
S_{t-5}	-0.016	-1.55	-0.048	-4.83	-0.049	-4.86
S_{t-6}	-0.042	-3.79	-0.045	-4.16	-0.051	-5.06
R^2	-	0.07	-	0.11	-	0.12
Volume	-	75.67	-	133.50	-	122.45
Volatility	-	67.55	-	83.42	-	89.44
Spread	-	35.52	-	43.15	-	43.63

The table reports coefficients from a a regression of order book depth on trading volume, absolute returns and spreads. V_t is defined as the sum of market buy and market sell volume in a given interval. Buy/sell depth is measured as the quantity available in the order book at or within k ticks from the best limit buy/sell price. The depth variables used here are sums of buy and sell side depth for $k = 2,6,10$. Hence, 2-tick depth is equal to $d^b(2)_t + d^b(2)_t$. The data upon which the VAR is estimated is sampled on a 20 second calendar-time basis and only observations between 6 and 18 GMT are employed. Prior to estimation the repetitive intra-day pattern is filtered from all variables. All t-statistics and χ^2-statistics are based on Newey-West heteroskedasticity and autocorrelation robust standard errors. The rows headed volume, volatility and spread give χ^2-statistics relevant to the null that coefficients on all current and lagged values of this variable are zero.

Table 9: Regressions of buy and sell depth measures on buy and sell volume, volatility and spreads

Regressor	2-tick buy depth		2-tick sell depth		6-tick buy depth		6-tick sell depth		10-tick buy depth		10-tick sell depth	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
V_t^B	-0.019	-1.31	-0.026	-1.78	-0.075	-3.53	-0.017	-0.84	-0.105	-3.88	-0.012	-0.51
V_{t-1}^B	0.082	4.93	-0.028	-1.98	0.181	9.47	-0.058	-3.05	0.187	7.86	-0.082	-3.71
V_{t-2}^B	0.065	4.31	0.016	1.20	0.128	6.70	-0.005	-0.29	0.147	6.08	-0.013	-0.6
V_{t-3}^B	0.084	5.91	0.009	0.70	0.170	8.98	-0.025	-1.46	0.215	9.01	-0.023	-1.19
V_{t-4}^B	0.051	3.35	-0.018	-1.39	0.138	6.77	-0.043	-2.46	0.16	6.81	-0.054	-2.68
V_{t-5}^B	0.055	3.40	-0.015	-1.13	0.140	7.11	-0.036	-1.87	0.171	7.81	-0.054	-2.3
V_{t-6}^B	0.043	3.01	-0.025	-1.83	0.118	5.71	-0.075	-3.69	0.168	6.81	-0.096	-3.96
V_t^S	-0.049	-3.40	-0.031	-1.64	-0.053	-2.42	-0.127	-4.95	-0.01	-0.36	-0.214	-7.43
V_{t-1}^S	-0.062	-4.30	0.112	6.85	-0.098	-5.23	0.146	6.46	-0.112	-4.88	0.131	5.03
V_{t-2}^S	-0.001	-0.09	0.054	3.30	-0.024	-1.26	0.104	4.99	-0.035	-1.58	0.115	4.57
V_{t-3}^S	0.007	0.49	0.077	4.84	-0.037	-2.08	0.146	7.35	-0.075	-3.48	0.144	5.66
V_{t-4}^S	0.006	0.42	0.045	2.94	-0.040	-2.14	0.153	7.28	-0.074	-3.37	0.175	6.98
V_{t-5}^S	-0.031	-2.17	0.027	1.57	-0.070	-3.57	0.130	5.37	-0.082	-3.59	0.164	5.61
V_{t-6}^S	0.010	0.73	0.053	3.23	-0.032	-1.62	0.146	5.60	-0.058	-2.38	0.197	6.34
$\lvert R_t \rvert$	-0.430	-5.07	-0.368	-3.99	-0.842	-6.95	-0.711	-5.54	-1.045	-7.53	-0.841	-5.81
$\lvert R_{t-1} \rvert$	-0.306	-4.01	-0.465	-5.58	-0.479	-4.18	-0.630	-5.64	-0.545	-4.1	-0.691	-5.61
$\lvert R_{t-2} \rvert$	-0.322	-4.49	-0.229	-2.92	-0.581	-5.03	-0.319	-2.73	-0.602	-4.23	-0.403	-3.23
$\lvert R_{t-3} \rvert$	-0.253	-3.52	-0.255	-3.63	-0.332	-3.23	-0.378	-3.80	-0.36	-2.77	-0.482	-4.18
$\lvert R_{t-4} \rvert$	-0.227	-3.35	-0.003	-0.05	-0.399	-3.84	-0.130	-1.28	-0.417	-3.46	-0.202	-1.73
$\lvert R_{t-5} \rvert$	-0.224	-3.07	-0.130	-1.61	-0.437	-3.85	-0.195	-1.68	-0.552	-4.3	-0.176	-1.29
$\lvert R_{t-6} \rvert$	-0.289	-3.66	-0.136	-1.81	-0.593	-5.14	-0.101	-0.93	-0.598	-4.71	-0.189	-1.48
S_t	-	-	-	-	-	-	-	-	-	-	-	-
S_{t-1}	-0.171	-2.67	-0.310	-4.89	-0.361	-3.79	-0.444	-4.93	-0.455	-4.04	-0.512	-4.73
S_{t-2}	-0.195	-3.30	-0.162	-3.01	-0.204	-2.48	-0.217	-3.07	-0.274	-2.69	-0.368	-4.28
S_{t-3}	-0.134	-2.39	-0.094	-1.84	-0.189	-2.56	-0.248	-3.81	-0.355	-3.81	-0.288	-3.73
S_{t-4}	-0.009	-0.18	-0.024	-0.44	-0.066	-0.91	-0.165	-2.35	-0.224	-2.36	-0.215	-2.65
S_{t-5}	-0.031	-0.53	-0.099	-1.88	-0.262	-2.92	-0.297	-4.34	-0.303	-2.91	-0.381	-5.03
S_{t-6}	-0.191	-2.96	-0.151	-2.70	-0.243	-2.41	-0.291	-3.93	-0.425	-3.64	-0.315	-3.97
R^2	-	0.06	-	0.05	-	0.11	-	0.10	-	0.12	-	0.1
Buy volume	-	100.80	-	17.20	-	287.58	-	27.58	-	266.7	-	33.61
Sell volume	-	33.25	-	96.21	-	43.88	-	197.64	-	44.7	-	243.17
Volatility	-	55.51	-	41.03	-	74.07	-	45.93	-	81.14	-	47.34
Spreads	-	20.67	-	35.61	-	19.44	-	50.71	-	23.73	-	45.46

The table reports coefficients from a regression of buy/sell depth on buy and sell volume, absolute returns and spreads. Buy/sell depth is measured as the quantity in the order book at or within k ticks from the best limit buy/sell price. The depth variables used here are for $k = 2, 6, 10$. The data upon which the VAR is estimated is sampled every 20 seconds and only observations between 6 and 18 GMT are employed. Prior to estimation the repetitive intra-day pattern is filtered from each variable. All t-statistics and χ^2-statistics are based on Newey-West heteroskedasticity and autocorrelation robust standard errors. The rows headed volume, volatility and spread give χ^2-statistics relevant to the null that coefficients on all current and lagged values of this variable are zero.

Figure 1: Intra-day activity patterns in spreads and trade frequency

Figure 2: Intra-day activity patterns in limit buy depth

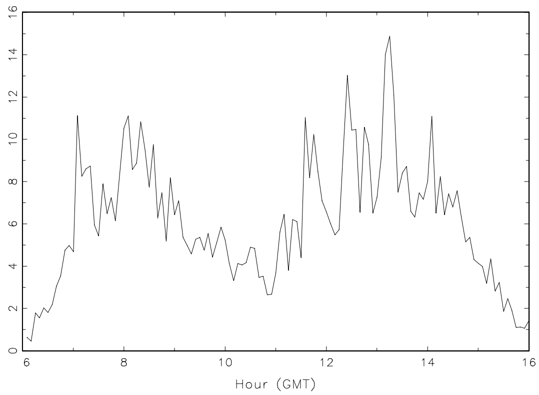
Figure 3: Limit Order Characteristics and Quantity Position

The x–axes give the quantity position of a limit entry computed as the aggregate quantity ahead of the incoming order in the execution queue. The observations were fitted with a weighted spline, where the weight is the entry probability. The dotted lines are 2 standard error bands, where the s.e. is computed using the weights.

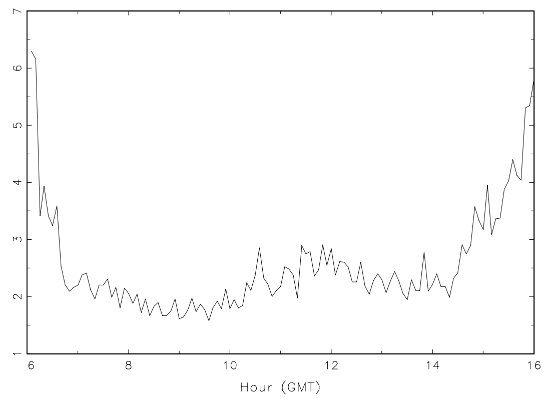
Figure 4: Limit Order Characteristics and Price Position

The x–axes give the price position of a limit entry computed as the difference (in ticks) between the incoming limit price and the previous best price. Price improvements are defined as positive for both limit buys and sells. The observations were fitted with a weighted spline, where the weight is the entry probability. The dotted lines are 2 standard error bands, where the s.e. is computed using the weights.

Figure 1:

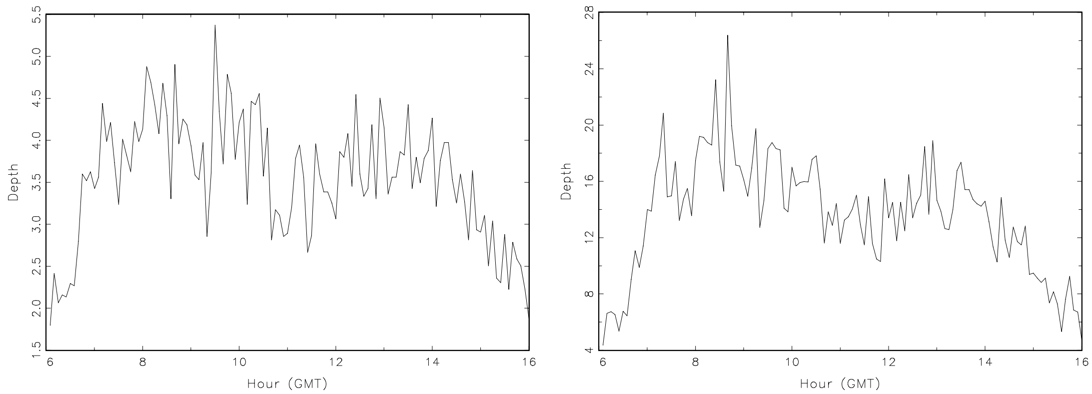


(a) Trade frequency



(b) Bid-ask spread

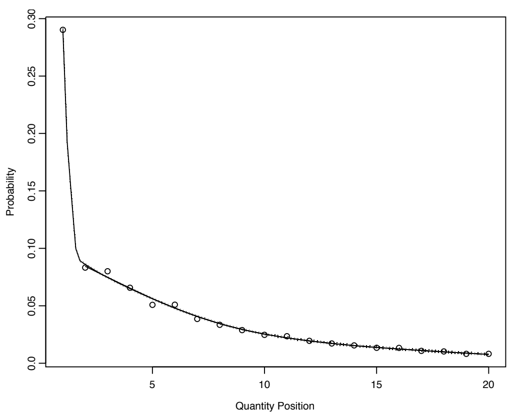
Figure 2:



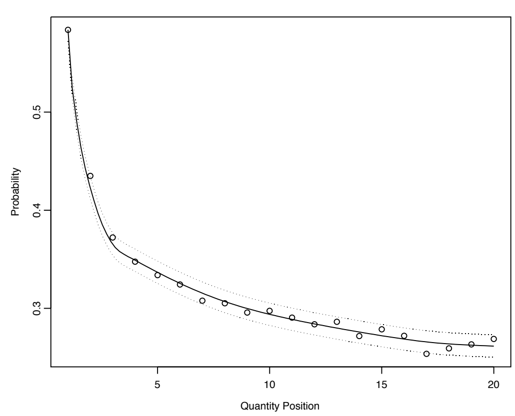
(a) Depth at best

(b) Depth at and within 4 ticks

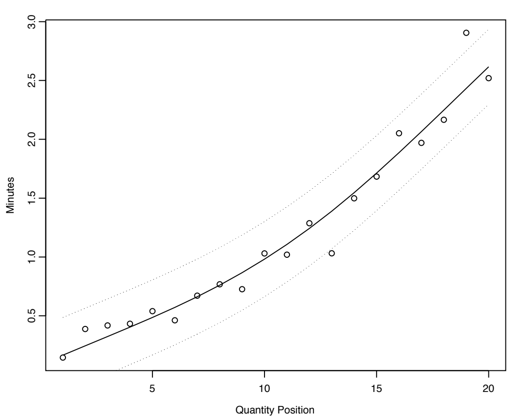
Figure 3:



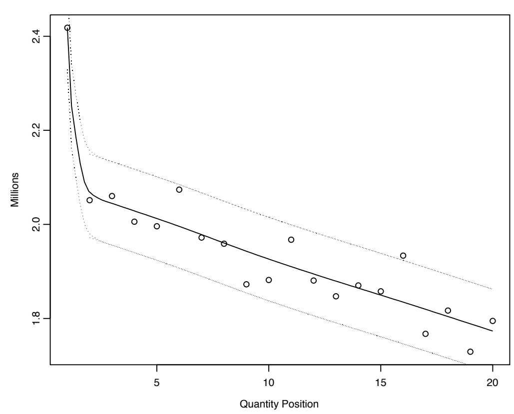
(a) Entry probability



(b) Trade probability

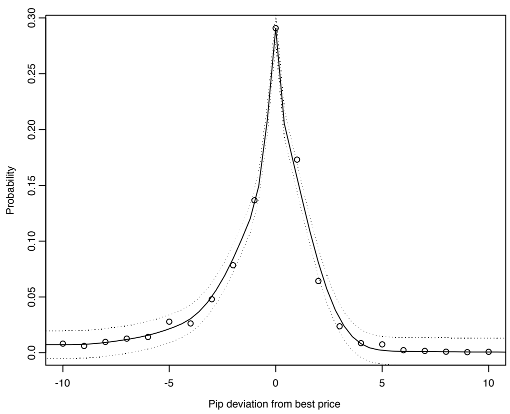


(c) Average lifetime

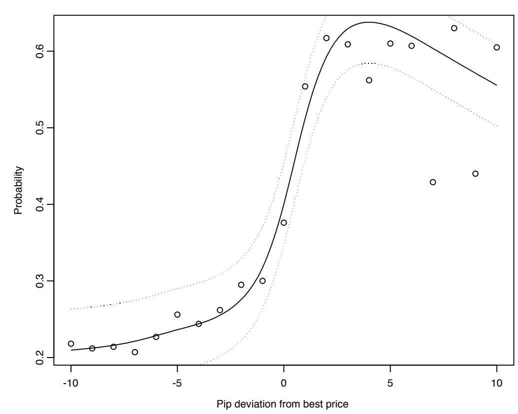


(d) Average size

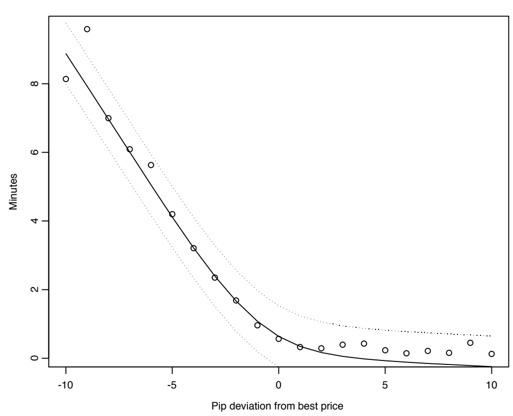
Figure 4:



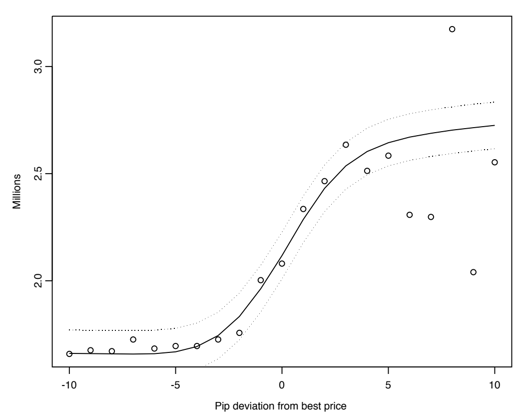
(a) Entry probability



(b) Trade probability



(c) Average lifetime



(d) Average size